DSD variability: normalization and retrieval

A. Berne and T. Raupach

Environmental Remote Sensing Laboratory
EPFL, Lausanne, Switzerland

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ÉCOLE POLYTECHNIQUE
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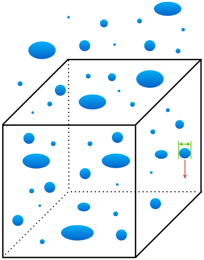
The raindrop size distribution (DSD)

- Concentration in air of raindrops with equivolume diameter in $[D, D + dD)$:

$$N(D)\,dD$$

- Weighted moments $\rightarrow$ rainfall variables.
- Measured at point scale by disdrometers.
- DSD variable in space and time $\rightarrow$ various normalizations.



Double-moment normalization of the DSD

The n^{th} moment of the DSD is $M_n = \int_0^\infty D^n N(D) dD$ $\quad [\text{mm}^n\ \text{m}^{-3}]$

With moment orders i & j, DSD can be written (**Lee et al. JAM 2004**):

$$N(D) = M_i^{(j+1)/(j-i)} M_j^{(i+1)/(i-j)} h(x),$$

where x is a normalized diameter:

$$x = D M_i^{1/(j-i)} M_j^{-1/(j-i)}.$$

To estimate the DSD we need three ingredients: h M_i and M_j

- How variable is the double-moment normalized DSD h in space?
- Can the double-moment normalization be used for radar DSD retrieval?

Instrument networks

Maps ©Thunderforest (CC BY-SA), map data ©OpenStreetMap (ODbL)

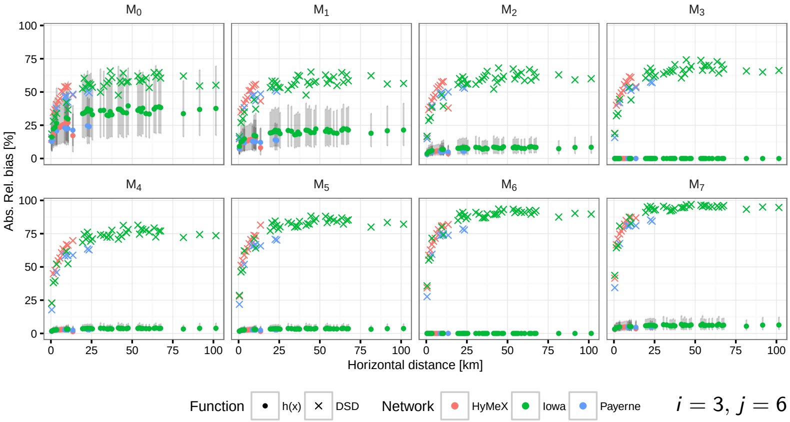
Instrument networks:

Ardèche, France
Payerne, Switzerland
Iowa, United States

$\sim$ 85% stratiform rain.

Google. Imagery ©2016 Data SIO, NOAA, U.S. Navy, NGA, GEBCO, Landsat, IBCAO, U.S. Geological Survey, Map data ©2016.

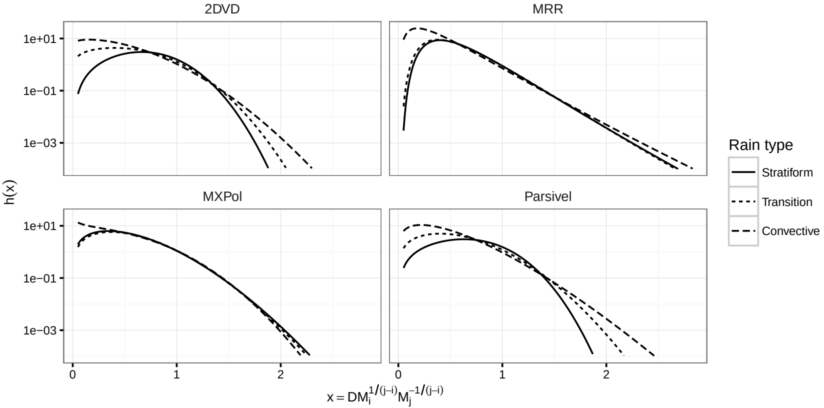
Changes in the horizontal



$i = 3, j = 6$

- normalized DSD "collapses" spatial variability.
- Similar for vertical variability (although larger remaining variability).

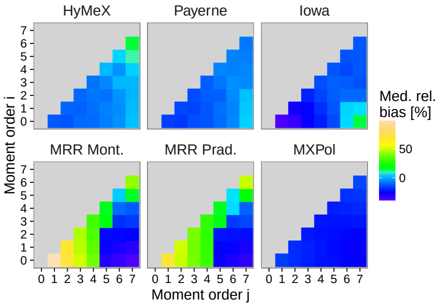
One fitted model per instrument type



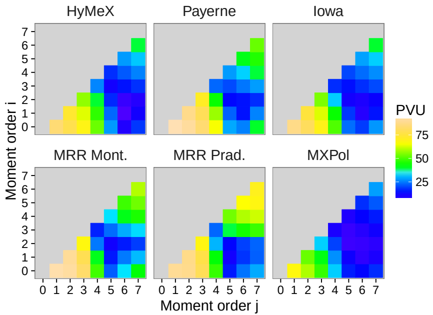
- Models trained on HyMeX (France) data only.
- Can they be used in other regions?

Performance by region in stratiform rain

Median rel. bias



% variance unexplained



- Model trained in France can be applied to other regions.
- Best performance with varied moment orders (e.g. 1 and 6).
- With best combination, $\geq$ 85% of DSD variance can be explained.

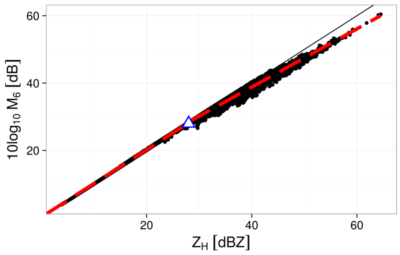
$\Rightarrow$ For DSD retrieval, h can reasonably be assumed invariant in space.

DSD retrieval

We have h, so we need two moments to retrieve the DSD.

Moment 6

- Retrieved using Z_h power laws.
- Split into two regimes at 28 dBZ (X-band).



Moment 3

- Z-weighted mean drop axis ratio $\widehat{r_m}$ estimated using Z_{DR}.*
- M_3 retrieved using $\widehat{r_m}$ and K_{dp}.
- Coefficients per raindrop axis ratio function.

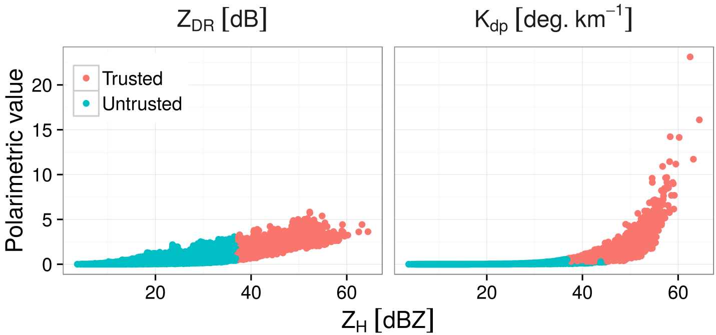
Parameterization

- 60% of DSDs from HyMeX, Payerne, and Iowa.
- Simulated variables at X-band.
- Temps. of 5, 10, and 15°C.

* See Jameson JAS 1983, Kalogiros et al, IEEE TGR 2013.

Dealing with radar noise

- Z_{DR} and K_{dp} can be noisy.
- Threshold on $Z_H < 37$ dBZ, $K_{\mathrm{dp}} < 0.3\ ^\circ\ \mathrm{km}^{-1}$, $Z_{\mathrm{DR}} < 0.2$ dB.
- In this case, Z_{DR} and K_{dp} predicted from Z_H.



DSD-retrieval method

Z_{DR}

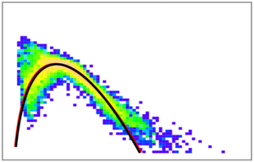
K_{dp}

Replace possibly noisy values

Z_h

Estimate moments three and six

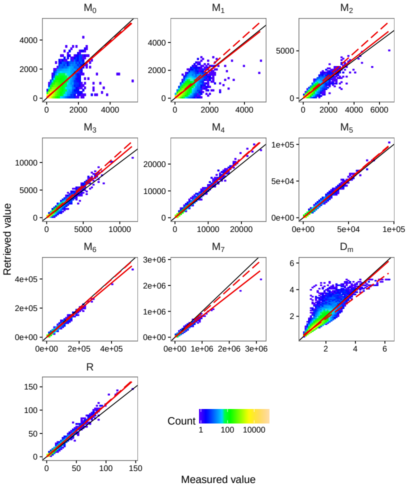
$\hat{h}(x)$ trained from observations, $i = 3, j = 6$



M_3, M_6, and $\hat{h}(x)$

DSD

Results with simulations

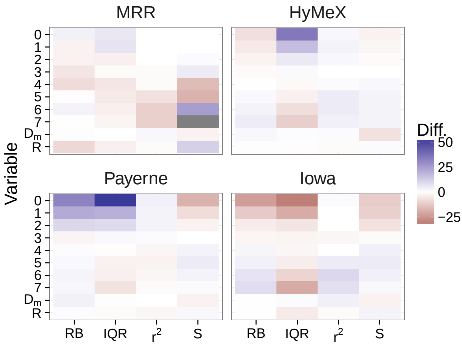


HyMeX results, Beard axis ratios.

- Simulated radar variables from disdrometer measurements.
- Compared against SCOP-ME (Anagnostou et al. AR 2009, Anagnostou et al. JH 2010, Kalogiros et al. IEEE TGRS 2013).
- Four different raindrop axis ratios (Beard 1987, Andsager 1999, Brandes 2002, Thurai 2007).
- Performances similar, on average DM has slightly lower bias for moments two to seven, D_m, R.

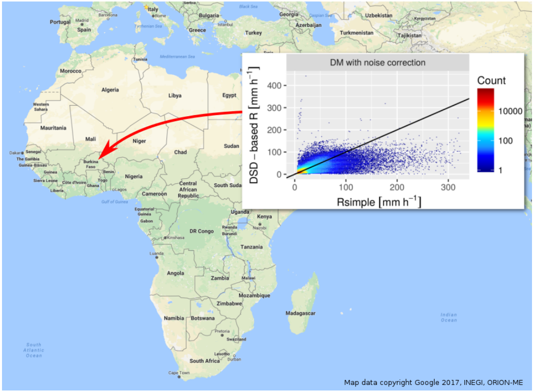
Results with real radar data

- Compared against Parsivels on ground in HyMeX, Payerne, and Iowa.
- In HyMeX, also compared against DSDs estimated aloft by an MRR (DM model trained for MRR data).
- Similar results for 2 algorithms; DM slighty better on MRR and Iowa data.



Reds show performance better with DM.

Tests in Africa



- X-band radar data from Burkina Faso.
- Provided by M. Gosset and M. Kacou (IRD, Toulouse, France).
- $h(x)$ retrained using local disdrometers.
- Promising results: DSD-based R matches closely to Z-R-based R.

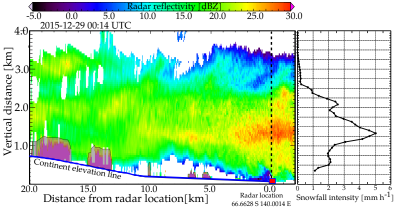
Conclusions

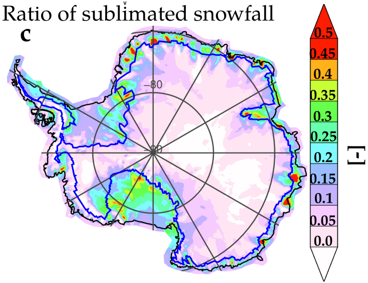
- Relative invariance of the double-moment normalized DSD $h(x)$.
- A new DSD-retrieval technique based on the double-moment normalization approach.
- Flexible, since there is no prescribed form of $h(x)$.
- Future work: remaining variability in $h(x)$, other radar wavelengths, other rain climatologies.

Raupach & Berne, *Invariance of the double-moment normalized raindrop size distribution through 3D spatial displacement in stratiform rain*, JAMC, 2017, 10.1175/JAMC-D-16-0316.1

Raupach & Berne, *Retrieval of the raindrop size distribution from polarimetric radar data using double-moment normalization*, AMT, 10, 2573-2594, 2017, amt-10-2573-2017

Precipitation and katabatic winds in Antarctica





Significant low-level sublimation of snowfall

(Grazioli et al., PNAS, 2017)

Poster initially planned yesterday, but now displayed on board #207 (thanks Walt!)

Thank you

Rainfall over mountains in Ardèche during HyMeX 2012 SOP

Moment 3 retrieval (1)

1. Retrieve radar-weighted mean raindrop axis ratio r_m [-] from Z_{DR}, using polynomial fit:

$$\widehat{r_m} = \sum_{i=0}^{5} c_i Z_{\mathrm{DR}}^{i}.$$

2. Use relationship between LWC and M_3 to derive (338.4 for X-band):

$$M_3 = \frac{338.4}{\widehat{C}} \frac{K_{\mathrm{dp}}}{(1 - \widehat{r_m})},$$

3. Polynomial fit and representative (mean) value of $\widehat{C}$ are parameterized per axis ratio function.

Moment 3 retrieval (2)

Liquid water content W [g m^{-3}] (with water density ρ_w g cm^{-3}):

$$W = \frac{\pi}{6} 10^{-3} \rho_w M_3,$$

and K_{dp} can be written (Jameson JAS 1985) :

$$K_{\mathrm{dp}} = \left(\frac{180}{\lambda} \right) 10^{-1} C W (1 - r_m),$$

with $C \sim 3.75$ (Bringi and Chandrasekar, 2001).